

# Automatic classification of volcanic tremor using Support Vector Machine

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**Abstract:** A system for automatic recognition of different volcanic activity regimes based on supervised classification of volcanic tremor is proposed. Spectrograms are calculated from volcanic tremor time-series, separated into four classes, each assumed as representative of a different state of volcanic activity, i.e., pre-eruptive, eruptive, lava fountains, and post-eruptive. As classification features, the spectral profiles obtained by averaging each spectrogram along its rows are chosen. As supervised classification strategy, the Support Vector Machine (SVM) classifier is adopted. Evaluation of the system performance is carried out on volcanic tremor data recorded at Mt Etna during the eruptive episodes of July-August 2001. The leave-one-out classification accuracy achieved is of about 94%.

## INTRODUCTION

In basaltic volcanoes, volcanic tremor is known to be a continuous seismic signal whose characteristics can be related to the activity regime of the volcano. Owing to its close relationship to the state of the volcano, volcanic tremor provides reliable information for alerting governmental authorities in case, for instance, of transition from a pre-eruptive to an eruptive regime. Furthermore, volcanic tremor monitoring yields information about the state of the volcano in time even when visual observation is hindered because of unfavorable weather conditions, or when direct access to the eruptive theatre is too risky. However, a huge amount of data is accumulated during continuous recording of volcanic tremor, posing severe difficulties for the human operator to handle these data masses on-line as well as off-line.

We propose automatic classification as a way to tackle those problems. Besides, automatic procedures are based on formalized data processing schemes, which render them reproducible. We thus can avoid the use expert's opinions which is always arbitrary to some degree. A scheme of the system proposed here is depicted in Figure 1. Data are represented by volcanic tremor time-series and their associated labels, namely, integer tags identifying the vol-



Fig. 1. Scheme of the proposed system.

canic activity regime during which they are recorded. Previous investigations highlighted that spectral analysis of tremor is particularly informative to discriminate different styles of volcanic activity [Falsaperla et al., 2005]. Therefore, we apply the Fourier transform to each time-series and calculate corresponding spectrograms using a gliding window scheme. The rows of each spectrogram are then averaged, thus ending up with patterns made up of average spectral values. For the classification of these patterns we adopted the Support Vector Machine (SVM) classifier [Vapnik, 1998]. Following a supervised learning scheme, during the SVM training phase the classifier learns how to discriminate the labelled pattern according to the extracted spectrogram-based features; then, during the test phase, its performance is evaluated on patterns not used during the training phase, but supposed to belong to the same parent population of the training set.

We present the application of the SVM classifier using the volcanic tremor data related to the 2001 Mt Etna flank eruption (Figure 2), which is one of the

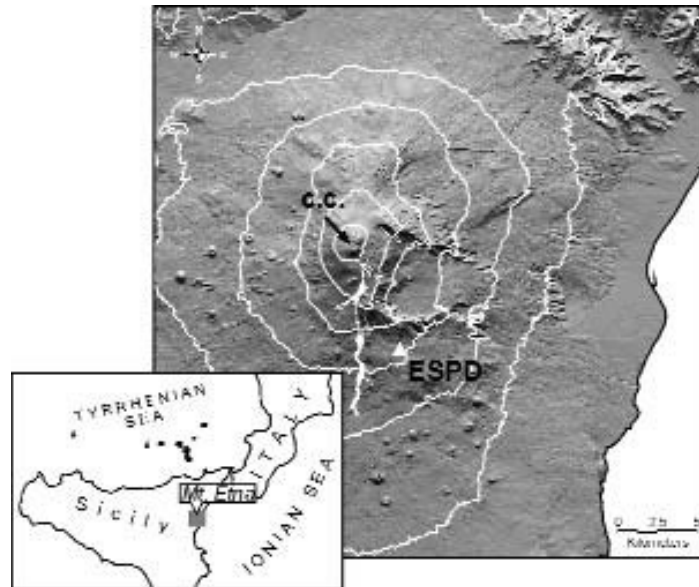


Fig. 2. Eruptive field at Mt Etna in 2001. C.C. stands for central craters. The white triangle marks the location of the seismic station ESPD.

most powerful ones occurred in recent years and for which a considerable amount of data is available.

### **DATA: THE CASE STUDY OF VOLCANIC TREMOR RECORDED DURING MT ETNA'S 2001 ERUPTION**

On July 17, 2001, a volcanic unrest began at Mt Etna, with episodes of lava fountains preceding and accompanying the onset of lava effusion. The effusive activity stopped on August 9, 2001.

To develop and evaluate the proposed system, a time-span covering 16 days before the onset and 7 days after the end of the eruption was chosen, i.e., July 1-August 15, 2001 (Figure 3). The volcanic tremor time-series recorded by the three component digital station ESPD, located at a distance of about 6 km from the summit craters (Figure 2), were considered. To each time-series we assigned a-priori labels depending on the recording date, namely: pre-eruptive (PRE) if data were recorded between 1 and 16 July; eruptive (ERU) if recorded between July, 17 and August, 8; post-eruptive (POS) if recorded between 9 and 15 August; lava fountain (FON) if recorded during lava fountain episodes. The latter ones occurred both during the pre-eruptive (July, 4, 5, 7, 12, 13, and 16) and eruptive stages (July, 17). The resulting dataset was composed of 153 PRE, 55 FON, 180 ERU, and 37 POS time-series.

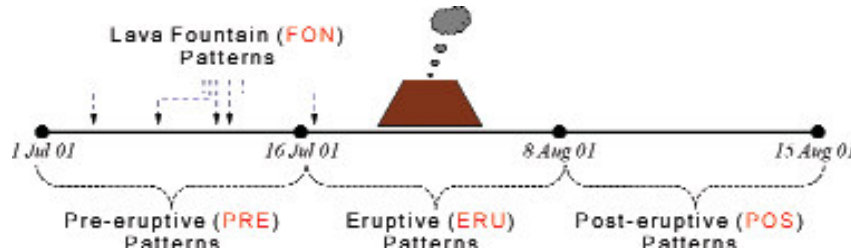


Fig. 3. Data. Scheme of the time-spans considered for Mt Etna's 2001 eruption.

### **FEATURES: AVERAGED SPECTROGRAMS**

For each time-series, the short time Fourier transform [Oppenheim and Schaffer, 1989] was calculated using time-windows of 1024 points with 50% of overlap. We extracted 62 frequency bins in the frequency range between 0.24 and ca. 15 Hz. The rows of each spectrogram were then averaged, so that the resulting patterns are made up by vectors of 62 average spectral values. These values were used as classification features. Figure 4 depicts a typical seismogram, spectrogram, and averaged spectrogram for each class.

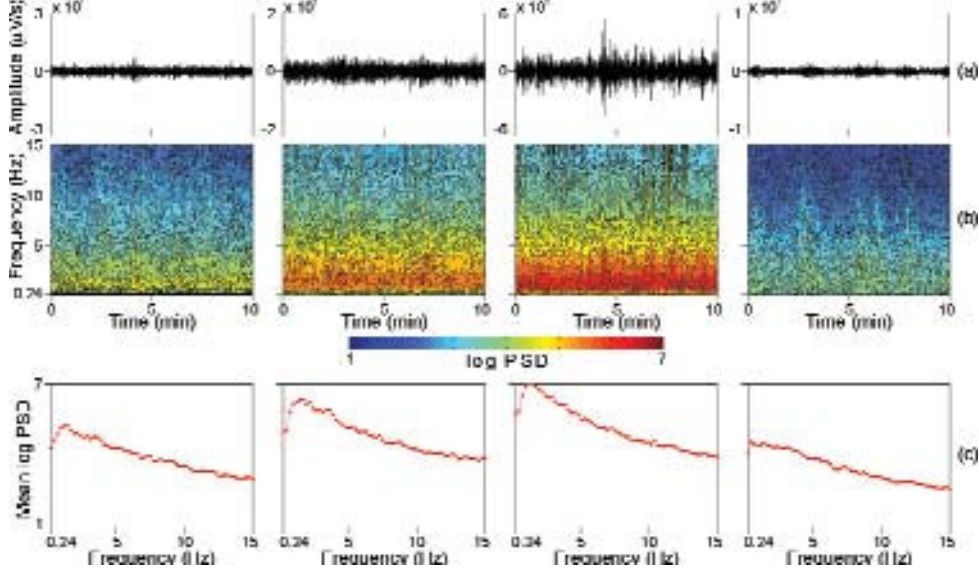


Fig. 4. Features. From left to right, examples of pre-eruptive, lava fountain, eruptive, and post-eruptive patterns: (a) time series, (b) spectrograms, and (c) corresponding 62-dimensional averaged spectrogram. PSD stands for power spectral density [from Masotti et al., 2006].

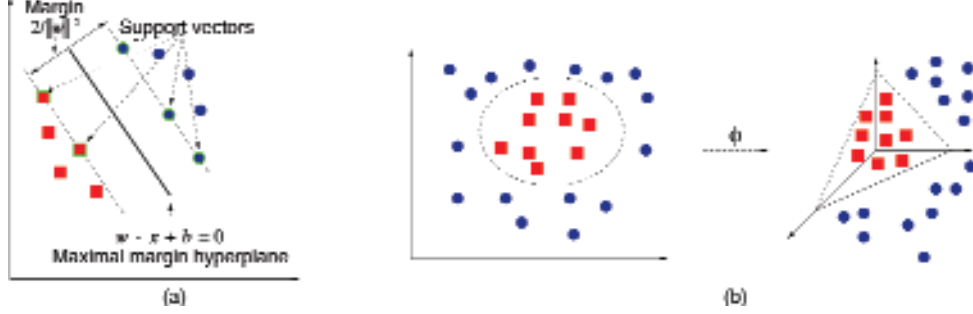
## CLASSIFICATION: SUPPORT VECTOR MACHINE

Each averaged spectrogram was then automatically classified as belonging to a specific class by means of a SVM classifier [Vapnik, 1998].

For a two-class classification problem, given a set of  $i = 1, \dots, l$  labeled patterns  $(x_i, y_i) \in \mathbf{R}^N \times \{1; -1\}$ , where  $x_i$  is the  $N$ -dimensional feature vector associated with the  $i$ -th pattern, and  $y_i$  the integer a-priori label assigned to its class membership, SVM training consists in finding the decision function  $f: \mathbf{R}^N \rightarrow \{1; -1\}$  which causes the largest separation between itself and the border of the two classes under consideration (Figure 5a). This decision function, also known as maximal margin hyperplane, is calculated in terms of some scalars  $\alpha_i$  and  $b$  by solving a quadratic programming problem and is defined by few patterns, the so-called support vectors [Vapnik, 1998]:

$$f(x) = \text{sgn}(w \cdot x + b) = \text{sgn}\left(\sum_{\text{Support Vectors}} y_i \alpha_i (x \cdot x_i) + b\right) \quad (1)$$

As the maximal margin hyperplane calculated by SVM is the farthest from the classes in the training set, it is also robust in presence of previously unseen patterns, achieving excellent generalization capabilities. Once SVM training is



**Fig. 5.** Classification. Maximal margin hyperplane found by SVM **(a)**; the green bordered patterns on the two margins are called support vectors and are the only ones contributing to the determination of the hyperplane. Transformation of a non-linear classification problem into a linear one applying the kernel function  $\phi$  **(b)**.

completed, SVM testing consists in assigning a label to a pattern  $x$  not used for training according to its position, in the feature space, with respect to the maximal margin hyperplane. SVM performance is hence evaluated by comparing the a-priori label of each pattern used for test with that assigned to it by the classifier.

The two-class approach described above can be extended to any  $k$ -class classification problem by adopting methods such as the one-against-all or the one-against-one, which basically construct a  $k$ -class SVM classifier by combining several two-class SVM classifiers [Weston and Watkins, 1999]. In this work, the one-against-one approach was used, namely, SVM classifier was trained six times, each time on averaged spectrograms  $x_i$  from two classes only, i.e., PRE vs. FON, PRE vs. ERU, PRE vs. POS, FON vs. ERU, FON vs. POS, and ERU vs. POS. A test pattern  $x$  was then associated with the class to which it was more often associated by the different SVM classifiers.

When patterns are not linearly separable in the feature space, a non-linear transformation  $\phi(x)$  is used to map feature vectors into a higher dimensional feature space where they are linearly separable [Vapnik, 1998]. With this approach, classification problems which appear quite complex in the original feature space can be tackled by using simple decision functions, namely, hyperplanes (Figure 5b). To implement this mapping, the dot products  $x \cdot x_i$  of Eq. 1 are substituted by a non-linear function  $K(x, x_i) \equiv \phi(x) \cdot \phi(x_i)$  named kernel. Admissible and typical kernels are:

$$\begin{aligned} K(x, x_i) &= x \cdot x_i && \text{Linear} \\ K(x, x_i) &= (\gamma x \cdot x_i + r)^d && \text{Polynomial} \\ K(x, x_i) &= \exp(-\gamma \|x - x_i\|^2) && \text{Radial Basis Function} \end{aligned} \quad (2)$$

where  $\gamma$ ,  $r$ , and  $d$  are kernel parameters selected manually.

## RESULTS AND DISCUSSION

SVM performance was evaluated using a leave-one-out strategy [Efron and Tibshirani, 1993] singularly over the patterns associated with each component: EW, NS, and Z. Hence, for each component, the classifier was trained exclusively with all patterns, except one used for test, belonging to that component. By changing the test pattern in a round-robin manner, training and test were repeated a number of times equal to the number of patterns of that component. Classification performance was then obtained as the sum over the three components of correctly classified test patterns. The classification results achieved by adopting a polynomial SVM kernel with  $d = 3$ ,  $\gamma = 10$ , and  $r = 0$  are depicted in Figure 6; here, colors represent the a-priori class memberships, whereas values on the  $y$ -axis the assigned ones. The choice for the SVM parameters is the result of some initial trial-and-error experiments. We summarize the results of our classification with a confusion matrix (Table 1). Rows and columns of this matrix are read as the a-priori and assigned class membership, respectively. Diagonal elements represent correctly classified test patterns whereas the off-diagonal elements are misclassifications. It turns out that the class membership assigned by SVM for a test pattern matches its a-priori class membership in 400 out of 425 cases, corresponding to a success of 94.1%. Namely, PRE patterns are correctly classified with a score of  $145/153 = 94.8\%$ , FON patterns  $42/55 = 76.4\%$ , ERU patterns  $177/180 = 98.3\%$ , and POS patterns  $36/37 = 97.3\%$ .

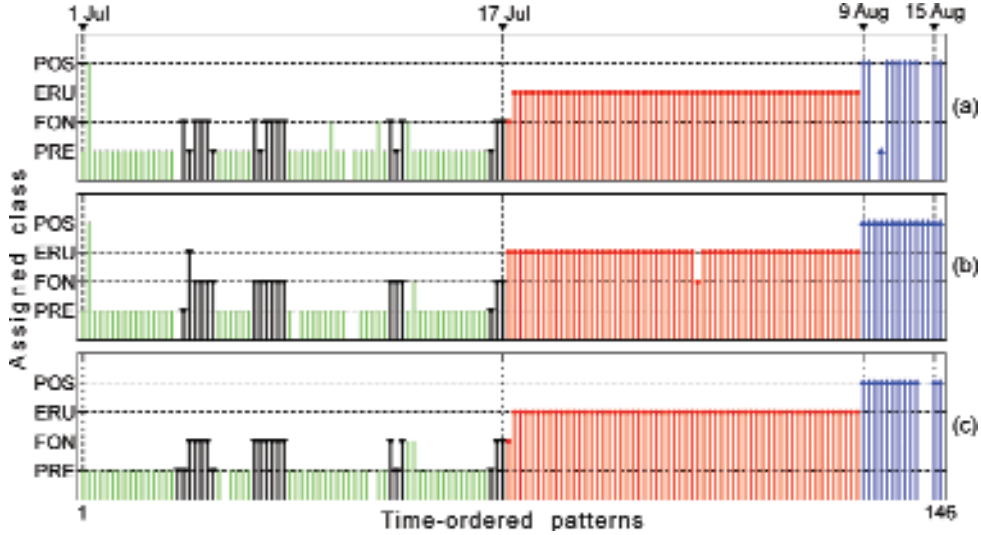


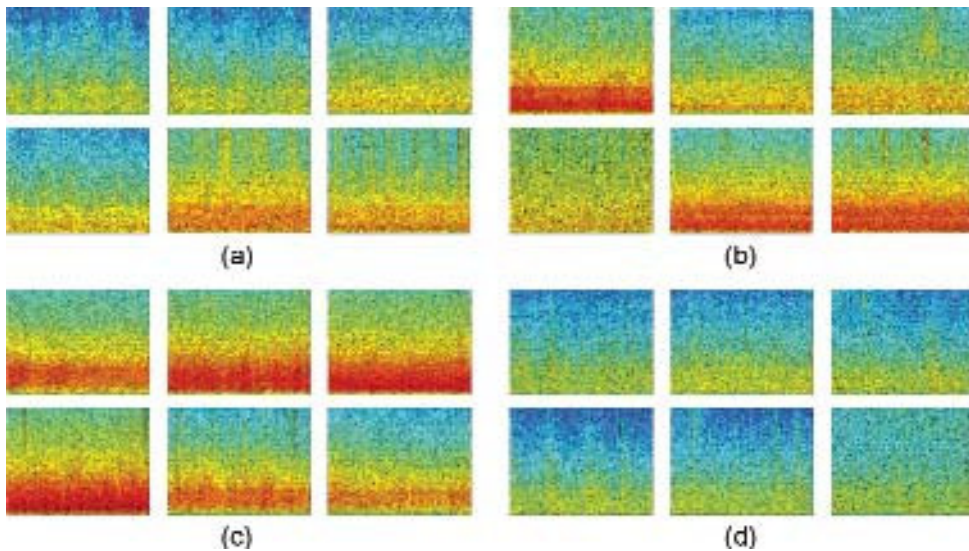
Fig. 6. Leave-one-out classification results for SVM over the patterns associated to each single component: EW (a), NS (b), and Z (c). Colors represent the a-priori class membership: PRE (green), FON (black), ERU (red), and POS (blue). Patterns are time-ordered. Gaps correspond to missing data. Arrows on top are time markers [from Masotti et al., 2006].



**Tab. 1.** Confusion matrix for SVM classification.

		Assigned class			
		PRE	FON	ERU	POS
A-priori class	PRE	145	6	0	2
	FON	12	42	1	0
	ERU	0	3	177	0
	POS	1	0	0	36

Looking at Figure 6, it is evident that misclassifications are mostly concentrated near class transitions, particularly between PRE and FON, but also between FON and ERU. This is the case, for example, of misclassifications associated with the transition between PRE and the first (or third) FON, as well as those associated with the first ERU pattern. A possible reason for that may be the intrinsic fuzziness in the transition from one regime to the other. This yields a non-null intra-class variability likely responsible for the misclassifications afore-mentioned. In particular, by looking at the different spectrograms, it is evident that the intra-class variability of PRE and FON is quite high, (Figures 7a, 7b), with a high number of PRE very similar to FON and vice versa. Conversely, the intra-class variability of ERU and POS is much lower (Figures 7c, 7d), with just a few ERU similar to FON and very few POS similar to PRE.



**Fig. 7.** Intra-class variability. Examples of PRE (a), FON (b), ERU (c), and POS (d) spectrograms.

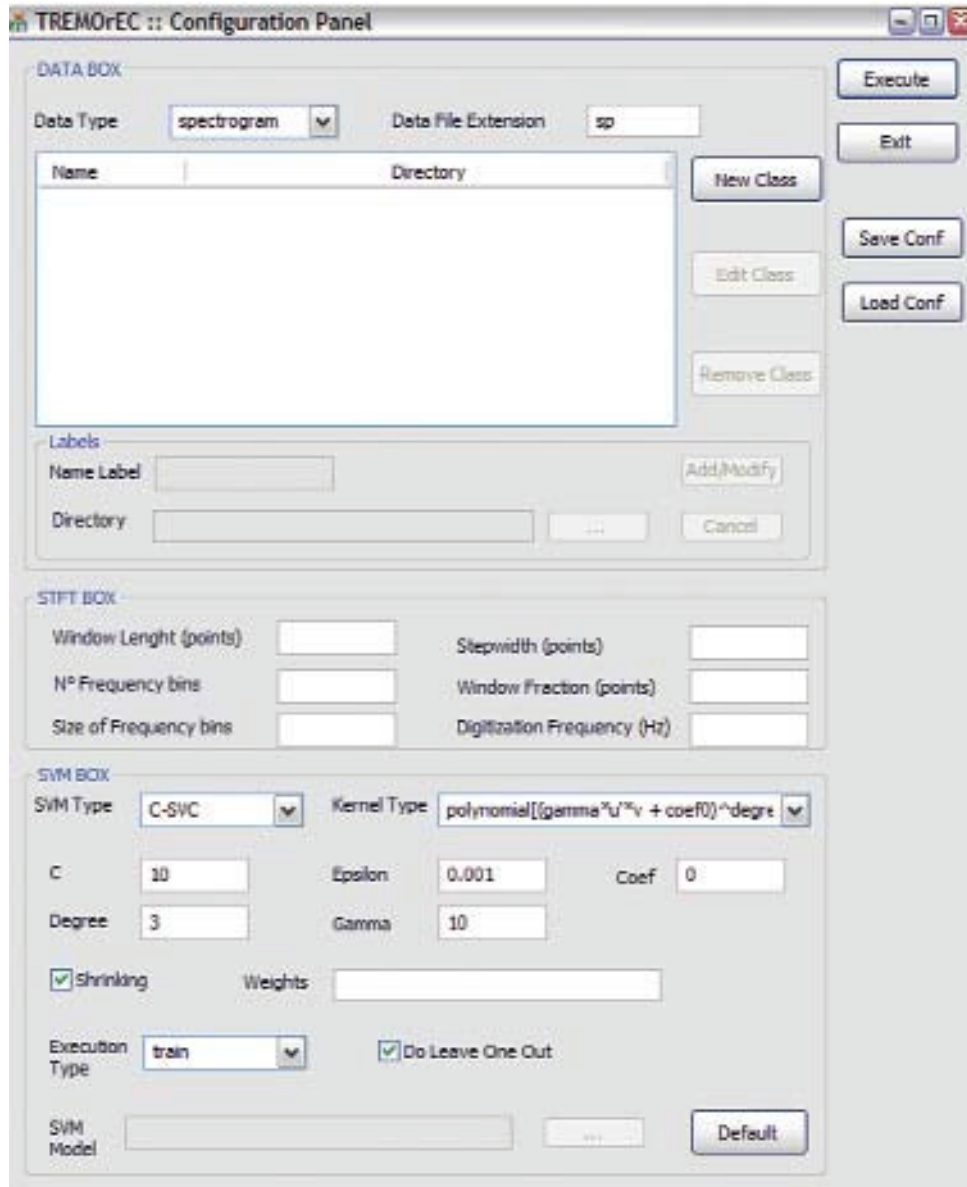


Fig. 8. TREMOREC.

## CONCLUSIONS

A system able to automatically recognize different volcanic activity regimes by means of supervised classification of the associated volcanic tremor was pro-



posed. Classification was performed using SVM as classifier and the averaged spectrograms of the original volcanic tremor time-series as features. By achieving less than 6% of classification error on volcanic tremor data recorded during Mt Etna's 2001 eruption, the performance of the proposed system results to be interesting. Useful applications can be envisaged for off-line classification of volcanic tremor datasets in search for precursors or in-depth investigation on the regime transitions. The developed approach can also be applied in other volcanic areas, where additional regimes may be taken into account or the same regimes may be associated with different volcanic tremor patterns.

The results presented in this report refer to the first test performed for this system [Masotti et al., 2006a; Masotti et al., 2006b]. However, to explore its generalization capabilities, further tests were performed on different eruptions, namely those occurred in 2002 and 2006 [Masotti et al., 2007a; Masotti et al., 2007c]. The obtained results showed good robustness of the system. Also, the performance of the SVM classifier was compared to that of artificial neural networks [Masotti et al., 2006c], showing outperforming results of the former. Finally, owing to the high classification performance achieved, and with the purpose of releasing a tool useful for the Italian Department of Civil Protection and scientific community, the initial Matlab implementation of the system was translated into a stand-alone software package (i.e., TREMOReC, see Figure 8) developed in Visual C++ as an executable for Microsoft Windows systems [Masotti et al., 2007b].

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